An Exploratory Analysis of Determinants and Effectiveness of Advertising on eBay

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This study was an exploratory analysis of determinants and effectiveness of advertising on eBay. This study employed principles of signaling theory to examine and test the selection and impact of advertising tools on eBay. Consistent with this theory, we predicted that advertising vehicles high in informational value would be used more extensively by sellers. We also predicted investments in informational advertising would be especially preferred by sellers who enjoy high seller ratings because such sellers can make more credible statements. Informational advertising was also expected to increase with the level of price variation and competitive intensity in the market. We also predicted advertising intensity would depend on the cost of the advertising and the extent to which such costs can be allocated across items in multiple listings. Finally, we hypothesized auction outcome would be driven primarily by prices and shipping costs, rather than by advertising vehicles. The hypotheses were tested using an extensive dataset of real auction data for a new electronic GPS device. Empirical tests showed good support for the hypotheses overall. An important contribution of this paper is that it is the largest exploratory analysis of advertising on eBay ever conducted. In this text, implications for advertising on eBay are discussed.

INTRODUCTION

eBay is the leading consumer-to-consumer online commerce community in the world. In the 3rd quarter of 2007 (July–September), eBay successfully sold US$14.4 billion in items across 556 million listings.[1] Such trading volume establishes eBay as the largest single online marketplace by far. In comparison, the retail size of e-commerce in the 3rd quarter of 2007, as estimated by the U.S. Census Bureau, was about $34.7 billion.[2] When compared to the Census survey of some 12,500 retailers, the eBay

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volume of transactions constituted more than 40% of the survey's online retail sales estimates. Furthermore, it is misleading to think of eBay as simply an outlet for individual consumers reselling items they no longer need, since a large portion of eBay transactions is generated by businesses both small and large alike. Even large national retail chains, such as Best Buy have eBay IDs and sell products using the eBay Web site.[3]

eBay earns revenue through listing fees and through the sale of various advertising vehicles. Such vehicles include those that help the listing stand out (*border*, *background*, *highlight*, *gallery*), provide areas for descriptive content or pictures of the item (*subtitle* or *gallery*), or position the listing highest in search results (*featured*). eBay also dedicates significant content and support to educating and encouraging its members to utilize these advertising tools.

Observation of eBay auctions indicates that these advertising vehicles are very popular. Most auctions employ one or more of these enhancements. Given the millions of auctions held on eBay at any given time, the revenue from advertising vehicles represents a significant income stream.

Despite this, there exists little research concerning the use and effectiveness of these vehicles in the marketing literature. In the largest empirical investigation to date, Li, Srinivasan, and Sun (2009) tested a variety of auction features on outcomes but did not control for the most common promotional vehicles such as border, background, and highlight. Li et al. conducted their study on a 2001 dataset; at that time many of the currently used promotional tools were simply not offered by eBay. In contrast, this study focused on the mix of promotional tools currently employed by eBay. In their integrated review and extensive empirical examination, Song and Baker (2007) tested the impact of pictures but, as was the case with Li et al. (2009), did not control for or test other advertising or promotional elements.

Therefore, the objective of this research was to offer a theoretical framework through which to examine and test the selection and impact of advertising tools on eBay. In order to test proposed effects, the study employed a comprehensive dataset of auction data downloaded from the eBay Web site for a commonly auctioned electronics product.

In the next section, we present principles of signaling theory as a theoretical framework through which to make some predictions. We pose exploratory research questions in the form of hypotheses. Following this, we describe the data and its collection in detail. Next, we present results of the analysis. The paper concludes with a summary of results and directions for future research. The authors stress that this paper is not an empirical application of signaling theory to advertising on eBay. Instead, this paper employs theoretical constructs of signaling theory to predict patterns of effects that are plausible according to this theory. In this sense, this paper is an exploratory study of marketing and advertising, not a study of economics.

SIGNALING THEORY

Product markets are sometimes characterized by conditions of information asymmetry. Information is asymmetric when sellers do not reveal the true quality of their products and buyers cannot readily determine product quality without first buying and then trying the product. In markets characterized by information asymmetry, consumers face the problem of being unable to distinguish high quality from low quality.

Akerlof (1970) showed how product markets break down due to information asymmetry: Sellers have an incentive to charge high prices for products which are actually of low quality and prefer to hold high quality items from the market. Consumers are naturally aware of this possibility and, therefore, do not trust sellers. As a result, consumers are unwilling to pay high prices for any product whose quality cannot be determined prior to purchase. Therefore, only low quality products ("lemons") are sold in the market.

However, through the mechanism of *signaling*, it is possible for firms to disclose real quality prior to purchase. Since buyers value high quality, vendors of high quality products have an incentive to inform consumers of the high quality of their brands using the signals available. A number of theories relating to various signals have been developed. These theories explore the signal value of price (Wolinksky, 1983), advertising (Nelson, 1974; Tellis & Fornell, 1988), warranty (Agrawal, Richardson, & Grimm, 1996; Grossman, 1981; Lutz, 1989; Spence, 1977), retailer reputation (Chu & Chu, 1994), brand name (Wernerfelt, 1988), and investments in intangibles, such as retail decoration (Klein & Leffler, 1981). A detailed discussion of the various arguments underlying signaling theory was provided by Boulding and Kirmani (1993). The following brief review is provided to show the conditions under which signals may be effective.

According to signaling theory, a signal is reliable if differential advantages exist between high- and low-quality vendors in terms of the costs of providing the signal. Costs could be the direct costs, such as buying use of or access to the signal (e.g., paying for the promotion), or indirect costs, such as servicing repair claims, handling complaints or returns, or risking reputation loss due to nonconformance with claims presented by the signal (e.g., promoting a high-quality product that is returned due to defects). Based on the relative cost advantage (or lack thereof) in sending signals, researchers have delineated between two situations in which the reliability of signals may differ.

Separating Equilibrium

When high-quality producers have a cost advantage over low-quality producers in sending the signal, the term *separating equilibrium* is used. This scenario is called *separating* because low-quality firms cannot copy the signal of high-quality firms, because the costs would be prohibitive. For example, a high-quality producer may offer a long warranty that a lower quality producer cannot mimic due to the high resulting service costs.

Pooling Equilibrium

When high-quality producers have no cost advantage in signaling the superior quality of brands, differentiation between high- and low-quality producers cannot occur. The situation is called *pooling* because vendors use the same signals and consumers cannot discriminate between high- and low-quality offerings. Pooling equilibrium can exist when low-quality firms advertise or promote using the same rate schedule as high-quality producers but do not intend to provide high-quality services for the long term. Alternatively, a low-quality firm may mimic long warranty terms but have no intention of actually servicing warranty claims.

SIGNALING THEORY AND ADVERTISING ON EBAY

The online auction environment available on eBay provides an excellent market through which to examine advertising on eBay. A visit to eBay reveals extensive use of a variety of advertising vehicles. Table 1 shows the advertising tools that a marketer may select, and their associated prices. A review of these tools indicates that these advertising vehicles may be used to either: (1) increase the visibility of display elements of the listing (*bold*, *border*, *highlight*), (2) provide additional textual information about product (*subtitle*), (3) provide a picture of the item to demonstrate its appearance and perhaps condition (*gallery or gallery plus*),[4] or (4) make the item easier to find upon search (*featured*). A detailed description of these vehicles is available on the eBay Web site (2008c) by visiting http://pages.ebay.com/help/sell/promoting_ov.html.

Signaling theory suggests that investments in these advertising vehicles will depend upon whether their use may result in separating equilibrium for high-quality firms. Advertising vehicles that can effectively distinguish high- from low-quality firms should be used to a greater extent than vehicles that are more likely to result in pooling equilibrium. Analysis of the advertising vehicles available on eBay suggests that display-type enhancements (*bold*, *border*, *highlight*) can be easily copied by low-quality firms in an attempt to fool consumers. These vehicles are all available at the same price schedule, regardless of seller reputation or real product quality. On the other hand, advertising vehicles that have greater informational value, such as *subtitle* and *gallery*, should be more powerful in creating conditions of separating equilibrium because they allow high-quality firms to offer more support (through text or image) of the value of their offerings. Therefore, we presented the following exploratory hypothesis:

> H1: Informational advertising signals are used more frequently than display advertising on eBay.

TABLE 1. Advertising vehicles available on eBay.

Feature	Description	Fee
Featured	In addition to being displayed in the search results, the listing will also be displayed in the top section of the search page. This form of promotion is only available to sellers whose rating is at least 10.	19.95
GalleryPlus	Creates a pop-up window displaying a larger gallery image file when a mouse pointer is moved over the listing on the search page.	0.75
Gallery	Enables the seller to display a small immage on the search page next to the title of the listing.	0.35
Highlight	Provides a color background to the title of the listing on the search page, effectively highlighting the listing on the search page.	5.00
Border	Provides a color border around the listing on the search page.	3.00
Bold	The title of the listing on the search page is in bold font.	1.00
Subtitle	The seller is allowed to enter an additional line of text to be displayed on the search page below the title of the auction.	0.50

According to signaling theory, as competition increases, firms will be required to make greater investments in signals that can effectively separate them from competitors. On eBay, competitive intensity can be seen in the frequency and number of listings for a particular item, and in amount of price variation across offers. eBay helps sellers easily gauge the amount and level of competition for a particular item. For example, eBay displays all listings completed within the last two weeks, and this price information is available to sellers prior to listing their items. In addition, when a seller submits a listing, eBay advises the seller about the past price distribution by providing the seller with the average price on recently completed auctions for similar items. As listing size and price variation increases, sellers will be inclined to justify and explain listings that may deviate from the mean. This will make investments in informational signals even more important. Therefore, the exploratory hypothesis was made that:

> H2: Use of informational advertising signals is positively correlated with price variability.
>
> H3: Listing size is positively associated with use of informational advertising signals.

After each auction, the buyer is given the opportunity to rate the seller. A positive rating is worth 1 point; a negative rating is worth –1 point, and a neutral rating is worth 0 points. These seller ratings are published online. In addition, eBay also provides the percentage of positive ratings earned by each seller. Because the use of *subtitle* and *gallery* represent potentially powerful informational vehicles, we expected that these vehicles would be used especially by sellers who have high ratings, since the information provided would be more credible and, therefore, assist in achieving separating equilibrium. Hence, we hypothesized that:

> H4: The better the reputation of the seller, the greater the use of informational signals.

In addition to product and seller characteristics, use of advertising vehicles on eBay will also likely depend upon their cost. For sellers, the cost of an advertising vehicle is likely considered relative to the price of the item being sold. Higher prices of the auctioned item may afford greater margins to pay for the investments in advertising. This will be the case regardless of the advertising element selected. Therefore, we expected that investments in advertising would increase with the price of the item being auctioned. We made the following exporatory hypothesis:

> H5: The higher the price of the auctioned item, the greater the investment in advertising vehicles.

eBay provides the possibility of achieving economies of scale in listing and advertising through the possibility of creating multi-item listings. The closing fees for single- and multi-item listings are identical. For instance, if one sells two $300 items in separate listings, one will pay the same closing fee of $20.50 as a seller who sold these two items in a single multi-item listing.[5] In addition, the insertion fee structure favors the multi-item listing. eBay has stated that the multi-item listing fee is capped at $4.80, regardless of the number of items and their value:

> The Insertion Fee for Multiple Item Auction (Dutch Auction) and Fixed Price listings is based upon the opening value of your items. The opening value is the starting or the fixed item price multiplied by the quantity of your items. The maximum Insertion Fee for any Multiple Item Listing is $4.80 (eBay, "Basic Fees Description", (2008a); see Melnik, Richardson, & Tompkins (2007), for further discussion of insertion fees).

In short, eBay's more generous terms with respect to listing multiple items represent in effect a quantity discount on advertising and insertion fees. To sellers of multiple items, this should be very appealing and increase investments in advertising vehicles as a result. Therefore, it was expected that:

> H6: The greater the number of items in a listing, the greater the investment in advertising vehicles.

Overall, then, we expected that advertising on eBay is a function of specific market and seller characteristics whose general pattern of results may be consistent with that predicted by signaling theory. Consistent with signaling theory, we predicted that informational signals would be used more often than display-type advertising, especially by sellers who have high ratings because such sellers are in a particularly strong position to gain an advantage from their use. We expected use of informational signals would also be driven by competitive intensity as expressed by variation in prices and supply of products in the relevant category. We also predicted that investments in advertising would be greater as its affordability increased, as is the case when average prices are high and/or the advertising investments can be spread across multiple item listings given eBay's flat rate policy.

While the pattern and use of advertising was expected to vary according to conditions described, we did not expect that advertising would be a very powerful force in determining auction outcome overall. In online auction environments, involvement is likely to be high, resulting in careful search regardless of the amount sellers advertise. For search-type goods, especially, auction outcome is likely to be determined by the relative prices and shipping costs offered by the sellers. Therefore, we hypothesized that:

> H7: Auction outcome will be determined by prices and shipping costs rather than by levels of advertising.

DESCRIPTION OF DATA

We focused our study on a commonly traded electronics product with a potentially wide range of consumers: the auto Global Positioning System (GPS) device. Auto GPS devices are relatively common on eBay. In fact, given their popularity, eBay has established a separate subcategory for auto GPS devices in its *consumer electronics* category. On any given day during our data collection period, over 3,000 listings for new (non-refurbished) auto GPS devices were available on eBay's Web site.[6] The overall number of available listings, including used and refurbished devices, surpassed 5,000.

Furthermore, these items are also sold by a number of different retail Web sites, which presents eBay sellers with an additional challenge: namely, competitive pressure from outside of the eBay community. This competitive pressure would most likely help to pull the price distribution closer toward the mean. The availability of retail prices also provided us with a price comparison basis for the items sold on eBay.

This large number of listings made these items an excellent sample for an empirical analysis, since a large enough dataset could be constructed over a brief period of time. The shorter the time period for the data collection, the less the likelihood that the data may capture unwanted external trends, such as changes in buyer behavior or external promotional effects.

For example, if one collects data over a period of one month, the prices of GPS devices may exhibit a significant downward trend and cause a change in the use of promotional tools. Furthermore, since other retailers also sell these items, substantial price fluctuations by those retailers can also significantly impact the data. By limiting our data collection time period to 2 weeks—and to a time period free of major shopping holidays in the United States—we limited the possibility of these effects. We also monitored the Web sites of BestBuy.com, OfficeDepot.com, and OfficeMax.com for any price changes.

Our empirical investigation was limited to only new devices and excluded used and refurbished items. In so doing, we effectively restricted ourselves to the case of homogeneous search-type goods, in that product characteristics do not vary across listings. This enabled us to reduce product-specific noise in the data when testing advertising effects.[7] Although this restriction may seem to reduce the signaling property of advertising, as the product condition is known in advance, there are still other aspects of an online consumer-to-consumer transaction that underscore the importance of signaling. For instance, the buyer has to trust the seller's description of the item and the seller's compliance with the terms of the transaction.

An important aspect of this study was the investigation of the effects of price distribution on the selection of advertising tools and the impact of those tools on auction outcome. In order to perform this analysis, our dataset needed to contain different price distributions. Using the GPS devices proved to be very useful, as there are numerous different models of GPS devices, each with its own unique price distribution.

Our dataset included 19 GPS models that were most commonly observed on eBay during the period of our data collection. Table 2 provides a list of these models and presents basic price statistics. The least expensive model in our dataset was the Garmin C330, with an average sold price of $141.60. The most valued model was the Garmin 770, with an average sold price of $648.78. In total, the dataset included 1,448 listings generated by 602 unique sellers. These listings were completed during a 2-week period between January 19, 2008 and February 1, 2008.[8]

Note that eBay removes all auctions from the accessible to the public section of its Web site two weeks after their completion.

In addition to the price characteristics, our dataset included a number of auction- and seller-specific variables, such as the *Closing_Time*, which is the time of day the auction closes (normalized to be between 0 [12:00 a.m.] and 1 [11:59 p.m.]); *Shipping*, the cost of shipping charged by the seller; *Rating*, the feedback score of the seller; and *Rating_Per*, the seller's percentage score of positive feedback. Seller's reputation in eBay auctions has received significant attention in the empirical economic literature and is an important control variable in our model (see Dellarocas and Resnick, 2003; Resnick, Zeckhauser, Swanson, & Lockwood, 2006; Reiley, 2000). *Sold*, a binary variable assuming the value of 1 if the listing resulted in a sale and 0 otherwise; and *FriSatSun*, a binary variable assuming the value of 1 if the listing ended on a Friday, Saturday, or Sunday. For further discussion of selection of control variables in eBay-based empirical studies, see Reiley, Bryan, Prasad, and Reeves (2007). Table 3 shows a summary of our statistics.

The dataset also contained a number of binary variables for various promotional features used by the sellers in our dataset. Table 4 shows the average values for these binary variables for each price distribution. These values effectively state the percentage use of these tools. For instance, in the case of Garmin 200W, 5.85% of all listings employed the *featured* option.

Table 5 provides price comparison across a number of popular retailers and also lists the manufacturers' prices. The comparison prices fully account for all available models and discounts during the period of our data collection. It is interesting to note that in almost all cases, the prices on eBay were considerably lower than those in major retail chains. There was only one exception to this: CircuitCity.com's price of the Garmin C330 fell below the average sold price on eBay after a $20 dollar mail-in rebate. However, even if we added the average shipping cost of $15.65 to the eBay prices, the gap would still remain in favor of eBay.[9] It should be noted that during the 2-week period of data collection, the retail prices of these models remained stable.

TABLE 2. Descriptive statistics.

GPS model	Obs. (total)	Obs.(sold items only)	Multi-Item Listings (number of listings)	Average Price (all listings)	Average Price (sold items only)*	St. Dev. of Price (sold items only)	Price Range (sold items only)
GARMIN							
200W	188	112	63	221.16	208.54	17.74	159.99 – 274.99
260	87	69	21	247.51	242.72	19.66	165.60 – 304.99
360	156	85	40	328.25	306.30	51.79	232.50 – 472.00
370	16	9	10	456.15	421.77	37.83	369.99 – 479.99
660	180	71	53	436.30	404.19	38.66	250.00 – 497.00
750	62	38	32	413.30	397.95	38.39	259.99 – 459.95
760	134	89	44	524.33	509.63	27.93	425.00 – 589.99
770	39	20	24	674.08	648.78	41.76	560.00 – 699.99
C330	43	35	0	146.74	141.60	20.19	89.99 – 177.50
C340	98	50	25	212.03	198.99	24.21	125.00 – 229.99
C530	63	22	13	213.56	197.04	24.17	157.50 – 229.99
C550	17	6	12	344.28	331.62	12.97	309.99 – 339.99
MAGELLAN							
3140	30	21	4	213.14	208.84	24.94	170.00 – 274.85
4040	48	35	8	276.18	248.85	33.60	132.49 – 290.00
4050	27	12	7	350.99	316.75	36.71	255.00 – 392.99
TOMTOM							
720	131	108	13	324.10	315.94	25.84	152.51 – 379.99
920	43	36	7	441.36	434.29	25.12	389.99 – 499.99
HP							
iPAQ 310	71	58	23	241.58	235.53	18.01	189.10 – 289.99
MIO							
C520	15	9	6	250.84	233.65	24.24	202.50 – 279.95

EMPIRICAL ANALYSIS

Over 95% of all listings in our dataset employed some form of advertising features on eBay. Many of these listings used two or more features. Table 6 displays the use of promotional tools in our dataset. The diagonal values simply show the number of listings using any particular feature and the off-diagonal cells show the overlap between any two features. It is obvious from the pattern of results that for the product in question, use of informational advertising, such as *subtitle* and *gallery*, was substantially more prevalent than display-type advertising. This finding was consistent with exploratory hypothesis H1 and suggests that informational advertising is preferred.

The substantial overlap among some advertising vehicles presented an identification problem, since features that overlap cannot be used in the same estimation equation. Observation showed, for example, substantial overlap for *featured* and *gallery*, *gallery* and *gallery plus*, *subtitle* and *featured*, and *subtitle* and *border*.

Because our investigation focused on the choice of advertising variables selected by the seller, we performed our empirical formulation using the following probit model:

$$Y = X\beta + \varepsilon,$$

TABLE 3. Descriptive statistics.

Variable	Average	St. Dev	Range	Obs.
Price	331.6279	124.7656	89.99 – 776.24	1448
Rating	5020.347	11574.61	0 – 322782	1448
Rating_Per	99.24993	2.023769	66.7 – 100	1432
Closing_Time	0.6056867	0.2097807	0 .001 – 0.999	1448
Shipping	15.65344	7.141374	0 – 65.45	1428
Sold	0.6111878			1448
FriSatSun	0.429558			1448

TABLE 4. Frequency of advertising vehicles.

GPS model	Obs.	Average Values for Binary Variables						
		Featured	GalleryPlus	Gallery	Highlight	Border	Bold	Subtitle
GARMIN								
200W	188	0.0585	0.0266	0.9468	0.0372	0.0426	0.1223	0.5426
260	87	0.1264	0.0575	0.9310	0.0000	0.0000	0.0805	0.5517
360	156	0.0577	0.0192	0.8462	0.0128	0.0192	0.0897	1.0000
370	16	0.3125	0.1250	0.9375	0.1250	0.1250	0.4375	0.6250
660	180	0.0833	0.0111	0.9167	0.0278	0.0222	0.0611	0.9944
750	62	0.1774	0.0806	0.9355	0.0161	0.0161	0.2419	0.5323
760	134	0.1045	0.0075	0.8284	0.0448	0.0448	0.1045	1.0000
770	39	0.1282	0.0256	0.7179	0.0513	0.1795	0.1282	1.0000
C330	43	0.0000	0.0000	0.8140	0.0233	0.0000	0.0000	0.0698
C340	98	0.1122	0.0306	0.9286	0.0408	0.0102	0.0816	0.5204
C530	63	0.0952	0.0000	0.9683	0.0159	0.0635	0.1270	0.6667
C550	17	0.2941	0.0000	1.0000	0.0000	0.0000	0.4706	0.7647
MAGELLAN								
3140	30	0.1333	0.0000	0.8333	0.0000	0.0000	0.0000	0.5000
4040	48	0.0625	0.0000	0.9375	0.0000	0.0000	0.1875	0.3750
4050	27	0.1111	0.0370	0.9630	0.0370	0.0741	0.2593	0.8148
TOMTOM								
720	131	0.0611	0.0611	0.9084	0.0229	0.0458	0.1527	0.4122
920	43	0.0930	0.0233	0.8837	0.0233	0.0465	0.3256	0.4186
HP								
iPAQ 310	71	0.0563	0.0141	0.8592	0.0282	0.0000	0.0282	0.3662
MIO								
C520	15	0.0667	0.0000	0.8000	0.0667	0.0000	0.0000	0.6667
ALL	1448	0.0898	0.0262	0.8964	0.0269	0.0318	0.1188	0.6720
Single-Item Only	1048	0.0057	0.0191	0.8884	0.0076	0.0105	0.0697	0.6078
Multi-Item Only	400	0.3100	0.0450	0.9175	0.0775	0.0875	0.2475	0.8372

TABLE 5. Retail price competition.

GPS model	Price					
	DATA Average price (sold items only)	Manufacturer's Web site	BestBuy.com	OfficeDepot.com	OfficeMax.com	CircuitCity.com
GARMIN						
200W	208.54	321.41	299.99			269.99
260	242.72	374.99	349.99	349.99		319.99
360	306.30	499.99				
370	421.77	599.99	599.99			599.99
660	404.19	749.99	499.99	649.99	899.99	
750	397.95	589.27	549.99		599.99	
760	509.63	749.99	699.99		799.99	699.99
770	648.78	964.27			999.99	
C330	141.60			299.99		129.99
C340	198.99		299.99			199.99
C530	197.04			299.99		
C550	331.62	482.13	449.99	389.99		349.99
MAGELLAN						
3140	208.84	349.99	249.99			
4040	248.85	449.99	299.99		499.99	
4050	316.75	499.99	499.99		699.99	399.99
TOMTOM						
720	315.94	449.95	449.99	449.99		419.99
920	434.29	549.95		549.99		
HP						
iPAQ 310	235.53	399.99	399.99			429.99
MIO						
C520	233.65		399.99			249.99

where Y = 1 if the advertising feature is being used and 0 otherwise.

Please note that in all of our estimations we used the White estimation technique in constructing robust standard errors, which are reported in all of our tables (see Greene, 2003). The heteroscedasticity correction was necessary, as we utilized observations drawn from 19 different distributions.

The aforementioned model was estimated separately for the various features for all of the listings. The independent measures included a number of auction and seller characteristics that might impact the choice of the advertising vehicle. We constructed the price distribution from successfully completed auctions for each GPS model. Our dataset captured three characteristics of the price distribution: the mean value (*Pmean*), the standard deviation (*St. Dev.*), and the opening price relative to the mean price of completed auctions of the model in question (*Opening2Mean*). We also calculated the number of completed listings (*Frequency*), which acts as a measure of supply and, therefore, as a measure of competition of the item on eBay.

We recognized that other characteristics may influence the choice of promotional tools, and we attempted to control for seller characteristics, such as the seller's experience on eBay (seller's rating and the percentage of ratings that are positive), shipping costs charged by the seller, and other auction characteristics (the closing time and day of the week). All of these variables have been shown to impact the buyer's decision and, hence, may play a part in a seller's choice of advertising tools.[10]

Given the infrequent use and considerable overlap of *highlight*, *bold*, and *border*, and considering the fact that these features are used simply to make a listing stand out in a search page rather than to provide information, we combined these features in constructing a new variable: *BBH* (*bold*, *border*, *highlight*). BBH assumes the value of 1 if the listing employed any one of these three features, and 0 otherwise.

We also created another new variable, *GS* (*Gallery Subtitle*), which equals 1 if the listing employed both the *Gallery* and *Subtitle* options, and 0 otherwise. This was done largely to account for the promotion available to eBay sellers during the time period of our data collection. During this

TABLE 6. Count of observations of use of various advertising tools.

	Featured	GalleryPlus	Gallery	Highlight	Border	Bold	Subtitle
Featured	130						
GalleryPlus	16	38					
Gallery	**130**	**38**	1298				
Highlight	31	16	37	39			
Border	29	17	46	20	46		
Bold	75	27	170	19	34	172	
Subtitle	*128*	26	895	*35*	*44*	147	973

time period, eBay allowed sellers to combine these two tools together in a *value pack*, for one price of $0.65, for a discount of about 25% relative to the combined cost of these two options. Thus, it was logical to assume that rational sellers who utilized both of these options did so as a pack (i.e., a single option). Also, both of these features are aimed at providing the buyer with additional information and, hence, are similar in their signaling property.

Observation of results for the complete dataset shown in tables 7a and 7b revealed very good support for the hypotheses overall. Consistent with exploratory hypothesis H2, we found that price variation (*St. Dev.*) resulted in significantly greater reliance on information signals (*GS* and *Subtitle*). This finding was also supported for *Opening2Mean*. For *Opening2Mean*, the magnitude of the coefficient suggests that a 10% increase in the opening price relative to the average price resulted in a 2.25% increase in the use of the *subtitle* feature. It appears that sellers who set their prices relatively high find it necessary to provide additional information to the potential buyer on the search page in order to induce the buyer to visit the auction page.

Consistent with H3, we found that as the number of completed auction listings in the category (*frequency*) increased, competitive intensity also resulted in significantly greater use of informational signals (*GS* and *subtitle*). Interestingly, a larger number of listings also induced a significantly greater reliance on the *bold* display vehicle, possibly in an attempt to make the item more visible.

H4 also received excellent support. Higher seller *rating points* drove significantly greater investments in informational advertising (*GS* and *subtitle*). In addition, it also resulted in a greater willingness to invest in the expensive *featured* advertising vehicle. These results were also found when using the *rating percent* measure as well. Interestingly, a higher *rating percent* also resulted in significantly greater use of the *bold* display advertising as well.

Consistent with H5, higher average prices did in fact make advertising more affordable and, therefore, attractive. Investments in informational advertising vehicles (*subtitle* and *GS*) and some display vehicles, especially (*border*), were significantly greater as average prices increase.

H6 also received excellent support. *Multi-item* auctions resulted in significantly greater investments in *all advertising vehicles*, as expected. For example, based on the average magnitude of the coefficients, we could conclude that multi-item listings were, on average, 17% more likely to utilize the *featured* option than the single-item listings.

We also tested these effects for multi-item listings separately. Descriptive statistics for multi-item listings across the models are shown in table 8. Results of the *probit* analysis are indicated in tables 9a and 9b. These results are consistent with those previously described. A unique variable in the multi-item analysis was *Number_in_Listing*, which represents the number of items offered in the listing. The coefficient on this variable is statistically significant and positive in all estimations. Interestingly, the magnitude of the coefficient increased with the cost of the promotional tool. Again, this was consistent with our hypothesis that investments in advertising vehicles are positively associated with the degree to which advertising costs can be spread out across multiple listings.

To H7, the probability of winning an auction was modeled as a function of opening prices, number of listings, retail reference prices, shipping

TABLE 7a. Probit results.

Variable	**Featured**		**BBH**		**GS**	
	b	dY/dX	b	dY/dX	b	dY/dX
Pmean	–0.00013	–6.30E–06	0.000718	0.000138	**0.001414**	0.000528
	(0.22)		(1.70)		(3.77)	
St. Dev.	–0.00402	–0.00019	–0.00358	–0.00069	**0.024119**	0.009011
	(0.58)		(0.72)		(5.76)	
Opening2mean	–0.13868	–0.00666	–0.21843	–0.0421	**0.438492**	0.163824
	(0.25)		(0.66)		(1.71)	
Frequency	**–0.00212**	–0.0001	**–0.00234**	–0.00045	**0.004037**	0.001508
	(1.96)		(2.98)		(6.07)	
Multi-item	**1.886154**	0.235364	**0.820362**	0.197602	**0.369657**	0.133113
	(10.42)		(7.87)		(3.90)	
ln (Rating+1)	**0.101554**	0.004874	0.014652	0.002824	**0.109693**	0.040982
	(2.68)		(0.64)		(6.32)	
Rating_Per	**0.243941**	0.011707	**0.164087**	0.031625	**0.061733**	0.023064
	(2.29)		(2.71)		(2.36)	
Shipping	–0.00014	–6.52E–06	**–0.01236**	–0.00238	**0.011129**	0.004158
	(0.02)		(1.87)		(2.04)	
FriSatSun	–0.08816	–0.00418	–0.06461	–0.01239	**0.157345**	0.058507
	(0.70)		(0.72)		(2.11)	
6 p.m. – 11 p.m.	0.050474	0.002472	–0.06508	–0.01235	0.064541	0.023999
	(0.35)		(0.65)		(0.80)	
Constant	–26.9149		–17.217		–8.93353	
	(2.52)		(2.84)		(3.42)	
Pseudo-R2	0.3699		0.1134		0.1648	
Observations	1413		1413		1413	

Note. Gallery was omitted as a separate estimation; Gallery was used in over 90% equaling 100%, causing problems with identification.

TABLE 7b. Probit results.

Variable	Subtitle		Bold		Border		Highlighted	
	b	dY/dX	b	dY/dX	b	dY/dX	b	dY/dX
Pmean	**0.003011**	0.000954	0.000665	0.000115	**0.001631**	7.04E–05	0.000644	2.16E–05
	(6.23)		(1.52)		(2.55)		(0.90)	
St. Dev.	**0.045066**	0.014607	–0.00281	–0.00049	–0.00125	–5.4E–05	–0.0061	–0.0002
	(8.00)		(0.56)		(0.15)		(0.69)	
Opening2mean	**0.865445**	0.225258	–0.16109	–0.02786	–0.85849	–0.03708	–0.83796	–0.02807
	(3.07)		(0.47)		(1.31)		(1.24)	
Frequency	**0.00554**	0.001777	**–0.00203**	–0.00035	4.18E–05	1.81E–06	0.000748	2.51E–05
	(7.51)		(2.49)		(0.03)		(0.55)	
Multi-item	**0.3857**	0.128553	**0.720889**	0.151669	**1.094942**	0.085023	**1.160504**	0.076352
	(3.57)		(6.47)		(5.49)		(5.35)	
ln (Rating+1)	**0.133443**	0.043956	0.019418	0.003359	–0.01551	–0.00067	–0.02865	–0.00096
	(6.89)		(0.82)		(0.38)		(0.67)	
Rating_Per	0.027759	0.008713	**0.145922**	0.025242	–0.0109	–0.00047	0.190692	0.006388
	(1.18)		(2.32)		(0.28)		(1.39)	
Shipping	0.009792	0.002957	–0.01122	–0.00194	**–0.02176**	–0.00094	–0.00707	–0.00024
	(1.58)		(1.64)		(2.16)		(0.66)	
FriSatSun	0.130912	0.040545	–0.01626	–0.00281	–0.13415	–0.0057	–0.10706	–0.00354
	(1.59)		(0.18)		(0.89)		(0.67)	
6 p.m. – 11 p.m.	–0.04181	–0.016	–0.16803	–0.02788	0.121897	0.005543	–0.08299	–0.00269
	(0.48)		(1.59)		(0.75)		(0.46)	
Constant	–7.00273		–15.6069		–0.48743		–20.3715	
	(2.97)		(2.48)		(0.13)		(1.49)	
Pseudo-R2	0.2877		0.0975		0.1547		0.1493	
Observations	1413		1413		1413		1413	

costs, seller ratings, and advertising variables using a *probit* model with several specifications. Results are shown in table 10. Note, all single-item listings that employed *featured* resulted in sale; thus the *featured* specification was excluded from the table.

Overall, the specifications captured substantial variation in predicting auction outcome. Overall, across the specifications, about 45% of variation was explained. The results revealed excellent support for H7. The probability of winning an auction was significantly and negatively impacted by higher opening prices (*Opening2Mean)*, shipping costs (*shipping),* and the number of available listings (*frequency*), which acts as a measure of supply. Interestingly, the probability of winning an auction was also significantly impacted by external retailer prices. It appears that potential buyers refer to external retail prices and have a significantly greater probability of buying the auctioned item the higher the comparative retail (*Retail_Price*) of the major electronic supplier, or the difference between the retail price and the average price on eBay (*Retail-Pmean*). It is important to note that advertising features (*subtitle*, *BBH*, *gallery*) exert no significant influence on the probability of sale.

Table 10 reveals what appears to be conflicting results concerning seller reputation: The percentage of positive ratings that a seller received (*Rating_Per*) had a significant and positive impact on the probability of sale in all specifications, while a seller's cumulative ratings points *(ln(Rating+1))* had a significant but negative impact in two of the four specifications. One would expect that cumulative ratings points would be positively associated with probability of completing a sale. However, this result may be explained by the fact that eBay is growing very rapidly, with more and more sellers entering the auction market. As the number of sellers increases, it may be that established sellers with more accumulated points face a lower probability of winning auctions, given the stiffer competition. This increase in competition would explain these conflicting findings. These findings also suggest that buyers on eBay may use the percentage positive of the seller's rating as the informational signal of the reliability of the seller.

TABLE 8. Descriptive statistics for multi-item auctions.

GPS model	Listings	Items per Listing			Succesful Completion		
		Average	St.Dev	Range	Average	St.Dev	Range
GARMIN							
200W	63	9.556	11.814	2 – 55	1.635	5.182	0 – 37
260	21	22.619	17.060	2 – 49	3.857	4.004	0 – 14
360	40	11.500	11.715	2 – 40	1.000	2.602	0 – 11
370	8	27.000	16.844	2 – 40	1.000	2.070	0 – 6
660	53	7.698	6.062	2 – 20	0.358	0.710	0 – 4
750	32	14.469	12.051	2 – 40	1.625	2.992	0 – 16
760	44	13.977	12.199	2 – 40	1.432	2.840	0 – 15
770	24	11.083	6.107	2 – 20	0.458	0.721	0 – 2
C330	0						
C340	25	17.000	15.324	2 – 50	2.520	3.721	0 – 14
C530	13	15.692	17.447	2 – 40	1.769	3.632	0 – 13
C550	12	16.583	12.944	2 – 30	1.167	1.586	0 – 5
MAGELLAN							
3140	4	10.000	0.000	10	1.750	2.217	0 – 5
4040	8	16.250	3.284	10 – 18	2.000	3.071	0 – 8
4050	7	14.714	5.880	4 – 20	0.000	0.000	0
TOMTOM							
720	13	12.769	9.791	2 – 30	3.231	5.036	0 – 18
920	6	26.000	31.956	7 – 90	7.333	8.869	1 – 25
HP							
iPAQ 310	21	5.048	5.599	2 – 27	1.143	1.014	0 – 3
MIO							
C520	6	7.833	6.735	2 – 20	1.000	2.000	0 – 5
All Items	400	12.703	12.596	2 – 90	1.540	3.467	0 – 37

TABLE 9a. Probit results for multi-item listings.

Variable	Featured		BBH		GS	
	b	dY/dX	b	dY/dX	b	dY/dX
Pmean	–0.0004	–0.00013	–0.0001	–3.4E–05	0.001811	0.000289
	(0.48)		(0.14)		(2.15)	
St. Dev.	0.005569	0.00177	0.000193	6.23E–05	0.002026	0.000323
	(0.55)		(0.02)		(0.24)	
Opening2mean	0.790359	0.251204	0.794105	0.256538	**1.749508**	0.27919
	(0.93)		(1.06)		(2.27)	
Frequency	0.001247	0.000396	–0.00072	–0.00023	0.001161	0.000185
	(0.78)		(0.52)		(0.78)	
Items_in_Listing	**0.110541**	0.035134	**0.054966**	0.017757	**0.108468**	0.01731
	(10.84)		(8.10)		(5.79)	
ln (Rating+1)	**0.193137**	0.061386	**0.1384**	0.044711	0.08152	0.013009
	(3.39)		(2.77)		(1.63)	
Rating_Per	**0.740703**	0.235422	**0.652388**	0.210756	0.140595	0.022437
	(4.48)		(5.06)		(1.11)	
Shipping	**–0.03679**	–0.01169	–0.01195	–0.00386	–0.00607	–0.00097
	(2.83)		(1.04)		(0.58)	
FriSatSun	–0.16474	–0.05166	–0.0356	–0.01147	0.24813	0.03817
	(0.89)		(0.23)		(1.45)	
6 p.m. – 11 p.m.	0.267289	0.088683	–0.12146	–0.0384	0.0359	0.005657
	(1.22)		(0.63)		(0.18)	
Constant	–77.8032		–67.9179		–17.4353	
	(4.64)		(5.24)		(1.38)	
Pseudo-R2	0.4672		0.2634		0.2418	
Observations	400		400		400	

TABLE 9b. Probit results for multi-item listings.

Variable	Subtitle		Bold		Border		Highlighted	
	b	dY/dX	b	dY/dX	b	dY/dX	b	dY/dX
Pmean	**0.004629**	0.000334	–0.0003	–7.6E–05	**0.00172**	0.000218	0.000532	0.000053
	(3.47)		(0.39)		(1.96)		(0.53)	
St. Dev.	0.019078	0.001375	0.003985	0.001008	0.004043	0.000513	–0.00213	–0.00021
	(1.66)		(0.43)		(0.37)		(0.18)	
Opening2mean	**2.361131**	0.170114	0.726531	0.183761	–1.22973	–0.15606	–0.29158	–0.02905
	(2.69)		(0.91)		(1.04)		(0.25)	
Frequency	0.002223	0.00016	–0.00125	–0.00032	0.002793	3.54E–04	**0.004881**	0.000486
	(1.32)		(0.83)		(1.54)		(2.45)	
Items_in_Listing	**0.112327**	0.008093	**0.054711**	0.013838	**0.029695**	0.003768	**0.04372**	0.004355
	(4.58)		(7.66)		(4.07)		(5.45)	
ln (Rating+1)	**0.163558**	0.011784	**0.202731**	0.051277	0.034816	0.004418	–0.09963	–0.00992
	(2.80)		(3.59)		(0.54)		(1.42)	
Rating_Per	0.083209	0.005995	**0.898061**	0.227146	0.115983	0.014719	0.245153	0.02442
	(0.62)		(5.00)		(0.87)		(1.48)	
Shipping	–0.01981	–0.00143	–0.00323	–0.00082	**–0.03686**	–0.00468	–0.01467	–0.00146
	(1.63)		(0.26)		(2.58)		(0.93)	
FriSatSun	0.311809	0.021227	0.04715	0.011987	–0.30406	–0.03677	–0.14192	–0.01378
	(1.52)		(0.28)		(1.47)		(0.64)	
6 p.m. – 11 p.m.	–0.21574	–0.01731	**–0.63605**	–0.13583	0.229252	0.031887	0.163516	0.017511
	(1.00)		(2.77)		(0.97)		(0.65)	
Constant	–13.9627		–93.1475		–12.7204		–25.9149	
	(1.04)		(5.17)		(0.95)		(1.56)	
Pseudo-R2	0.3787		0.3242		0.1211		0.1861	
Observations	400		400		400		400	

Finally, in an additional test of H7, we modeled willingness to pay as a function of advertising, seller, market characteristics, as well as external retail price. Note, we employed the Tobit model with a varying censoring point (see Amemiya, 1973), which enabled us to investigate these effects on the buyer's willingness to pay for the item. Listings that resulted in no sale are left-censored as the willingness to pay was below the listing price, while listings that ended with a buy-it-now option or any other form of a fixed price transaction are right-censored, as the willingness to pay was above the sales price. Auction listings are not censored, as the auction price represents the willingness to pay of the bidder with the second highest valuation. Results are shown in table 11.

As expected, we found that final auction prices are driven by external retailer prices and shipping costs. The data showed that for every $1.00 increase in external retail prices, willingness to pay on eBay increased by $0.63; shipping, on the other hand, showed a perfect trade-off: for every $1.00 increase in shipping prices, willingness to pay likewise decreased by $1.00. The effect of *BBH* showed only marginal statistical significance but the magnitude of the effect is trivial. It suggests that use of *BBH* resulted in an increase in willingness to pay of $10.92; however, this represents only about 3% of the average price. It is interesting to observe that seller reputation has no significant impact on willingness to pay higher prices. Thus, while having a higher percentage of positive ratings may influence choice of a seller, it does not mean that the selected seller can charge higher prices. Overall, these analyses provided further support for H7, in that they demonstrated that price and cost considerations, rather than advertising variables, were the dominant competitive factors.

CONCLUSION

This study was an exploratory investigation of the use of advertising tools on eBay. We presented several exploratory hypotheses regarding effects based on principles of signaling theory. It is important to stress that the goal of this study was not to empirically test signaling theory on eBay. Instead, this was an exploratory study that used signaling theory to predict

TABLE 10. Impact of variables on probability of sale of single item listings.

	Y = Sold		**Y = Sold**		**Y = Sold**		**Y = Sold**	
	b	**dY/dX**	**b**	**dY/dX**	**b**	**dY/dX**	**b**	**dY/dX**
Subtitle	–0.06876	–0.0192					–0.0511	–0.0143
	(0.52)						(0.39)	
BBH	0.327271	0.081209					0.3404	0.0840
	(1.50)						(1.56)	
Gallery	0.16841	0.049873	0.1569	0.0464	0.1751	0.0520		
	(0.93)		(0.88)		(0.98)			
Opening2mean	**–10.0317**	–2.81914	**–10.0550**	–2.8296	**–10.0866**	–2.8369	**–10.0542**	–2.8246
	(16.16)		(16.45)		(16.35)		(16.24)	
Frequency	**–0.00379**	–0.00107	**–0.0040**	–0.0011	**–0.0040**	–0.0011	**–0.0037**	–0.0011
	(3.39)		(3.76)		(3.72)		(3.36)	
ln (Rating+1)	–0.03827	–0.01075	**–0.0453**	–0.0128	**–0.0423**	–0.0119	–0.0382	–0.0107
	(1.61)		(1.97)		(1.83)		(1.62)	
Rating_Per	**0.039593**	0.011126	**0.0421**	0.0118	**0.0402**	0.0113	**0.0424**	0.0119
	(1.65)		(1.76)		(1.67)		(1.77)	
Shipping	**–0.01639**	–0.00461	**–0.0171**	–0.0048	**–0.0184**	–0.0052	**–0.0162**	–0.0046
	(2.04)		(2.17)		(2.33)		(2.02)	
FriSatSun	–0.10343	–0.02918	–0.1036	–0.0293	–0.1062	–0.0300	–0.0968	–0.0273
	(0.94)		(0.95)		(0.97)		(0.89)	
6 p.m. – 11 p.m.	–0.10139	–0.02889	–0.0754	–0.0214	–0.0885	–0.0252	–0.0971	–0.0276
	(0.88)		(0.66)		(0.77)		(0.84)	
Retail_Price			**0.0010**	0.0003				
			(2.66)					
Retail-Pmean	**0.002834**	0.000797			**0.0028**	0.0008	**0.0026**	0.0007
	(3.08)				(3.25)		(2.96)	
Constant	**7.215013**		**6.9573**		**7.2590**		**7.1027**	
	(3.03)		(2.94)		(3.05)		(2.97)	
Pseudo-R2	0.4543		0.4495		0.4524		0.4536	
Observations	1013		1013		1013		1013	

a plausible pattern of results for a commonly traded consumer electronics good. In order to isolate advertising effects, the study used auction data for a new item only. We predicted that advertising would focus on vehicles that provide more information. We also predicted that use of these informational advertising vehicles would increase with competitive intensity and be especially used by sellers who have high ratings because such informational advertising would have greater credibility. However, given that we limited our analysis to new items of a search-type good, we expected that the impact of advertising would be weak overall and that auction outcome would be driven primarily by price and cost considerations. We also predicted that investments in advertising would also be strongly influenced by advertising costs and the extent to which these costs could be spread out across multiple listings.

Our study employed a large dataset of real auction data recorded from the eBay Web site. When testing advertising effects, we controlled for a variety of effects, including seller reputation, shipping costs, auction time of day, auction day of week, external prices, number of completed auctions in the category, and the number of listings of the item. We also tested combined as well as separate measures of advertising variables across specifications.

Our results revealed excellent support for the expected patterns. We found that informational advertising was more prevalent than display-type advertising. Our analysis also showed that investments in informational advertising were preferred by firms who have higher seller ratings. However, advertising investments were ineffective in increasing the probability of sale. Instead, auction outcomes were determined primarily by prices and shipping costs. We also found that investments in advertising were strongly influenced by advertising costs and the degree to which such costs could be spread out across multiple listings.

These results suggest that advertising investments are made by firms in an attempt to signal quality, and that firms will employ vehicles that are best suited for this purpose according to market conditions and advertising costs. However, it appears that firms understand the limits of advertising; auction winners may not be able to pass along advertising costs to

TABLE 11. Impact of variables on willingness to pay.

Variable	Coefficient
	(t-stat)
Featured	17.26136
	(0.84)
BBH	10.91526
	(1.79)
GS	–1.896295
	(0.50)
Frequency	–0.041513
	(1.25)
ln (Rating+1)	–0.2054002
	(0.28)
Rating_Per	0.7888234
	(1.16)
Shipping	**–1.000835**
	(3.86)
FriSatSun	–5.224928
	(1.54)
6 p.m. – 11 p.m.	1.831352
	(0.51)
Retail_Price	**0.6335644**
	(57.62)
Constant	–14.95922
	(0.22)
Pseudo-R2	0.1639
Observations	1013

buyers and may have to assume these costs as a part of doing business. Results clearly show that the eBay markets for this particular product are very efficient: opening prices, external prices, shipping costs, and the relative supply of items all drove auction outcome. Although higher rated sellers enjoy some advantage in selection, they cannot charge more because of these ratings.

LIMITATIONS AND DIRECTIONS FOR NEW RESEARCH

In order to test advertising effects on eBay, we needed to control for product characteristics that might impact the selection and use of advertising vehicles. Our sample used an item which can best be described as a search-type good: the item was brand new, its features were well understood by potential buyers, and its performance was easily assessed through a variety of information sources and outlets. For search-type goods, one would expect that the use of advertising would tend toward information provision.

However, the markets of eBay are filled with of cornucopia of products, including more experience-type products, such as collectibles. For experience-type goods, it is likely that the use of advertising will vary significantly, perhaps with a greater focus on display-type enhancements such as *border*, *background*, or *highlight*. In addition, for more highly differentiated goods, prices may be more inelastic, shipping costs may matter less, and seller reputation may exert an even greater influence. Future researchers should investigate the degree to which this may be the case.

In this study, we also controlled for a variety of factors that might influence auction outcome, including the number of listings and seller ratings. It would be interesting to investigate the influence of these factors in a more systemic fashion by collection data that might allow for tests of differences across these variables. For example, although it is clear that the supply of items and external prices impacted auction outcome, future research might investigate whether competition on eBay also impacts external retailer competition as well. Our hypotheses are presented in an exploratory fashion because in this complex environment, interactive effects should also be measured. Although we controlled for variables as best we could in our linear model, interactive effects can influence outcomes. Although we believe signaling theory is a good start towards better understanding on eBay, other theoretical frameworks may provide better approaches.

Future research might also investigate what eBay's strategic goals are with respect to advertising vehicles. We have argued that display-type advertising is not very effective for search-type goods because it is weak in information provision. However, eBay could easily increase the power and effectiveness of display-type enhancements through a color-coding scheme. For example, eBay could offer sellers who have very high ratings the opportunity to buy a different color of *bold*, *background*, or *highlight* to clearly differentiate themselves from lower rated sellers. This would immediately infuse display enhancements with informational value. eBay has surely thought of this as well, but has not yet implemented such a method. Perhaps eBay fears a loss of advertising revenue as a result. Could it be that even market makers such as eBay may benefit from some level of market inefficiency so that larger advertising fees can be collected? Such an intriguing question is also worthy of future research.

Endnotes

1. eBay's *Third Quarter 2007 Financial Results,* available online at http://investor.ebay.com/financial_releases.cfm. See eBay (2008b).
2. Quarterly E-Commerce Retail Sales, 3rd Quarter of 2007, published by the U.S. Census Bureau based on a survey of about 12,500 retail firms and is available online at http://www.census.gov/mrts/www/data/html/07Q3.html
3. During the period of this study, Best Buy sold its merchandise under its eBay ID: *best_buy_outlet*.
4. From examination of individual listings, we even noticed that sellers of brand new items employed the use pictures as means of verifying that the item remains sealed in its original retail box.
5. A multi-item listing allows the seller to create a single listing for several identical items. Such a listing allows for multiple buyers. For example, a multi-item listing with three items can have up to three unique buyers.

6. The number of available listings included all listings closing within the next 10-day period.
7. For further discussion of homogeneous goods analysis in eBay-generated data, see Melnik and Alm (2002) and Melnik and Alm (2005).
8. Please note that for three models, due to technical issues with our collection method, the data was collected during the 2-week period of January 25, 2008 and February 9, 2008.
9. It is also important to note that eBay transactions are largely untaxed at the time of the sale, as many transactions tend to be across state lines, in which case the seller may not have the legal obligation to collect the tax (*Quill v. North Dakota,* 1992).
10. For examples of empirical studies into the buyer's behavior, see Reiley (2000), Reiley et al. (1999), and Resnick et al. (2006).

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